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Jupyter: Intro to Data Science - Lecture 11 Movie Reviews

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Data Dive 11: Movie Reviews

Today, we'll build a naive bayes classifier to judge whether a movie review is positive or negative. In today's exercise, we'll be using a sample of movie reviews compiled by Stanford University's CS Department (http://ai.stanford.edu/~amaas/data/sentiment/).

Courtesy of @AmznMovieRevws (https://twitter.com/AmznMovieRevws)

In [ ]:
```
import os
%matplotlib inline

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

from sklearn.feature_extraction.text import CountVectorizer
from sklearn.naive_bayes import BernoulliNB
from sklearn.model_selection import KFold, train_test_split
from sklearn.metrics import accuracy_score, recall_score, precision_score
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import GradientBoostingClassifier

random_state = 20181118
```

In [ ]:
```
corpus_df = pd.read_csv('https://grantmlong.com/data/sentiment_corpus.csv')
corpus_df.shape
```

Inspect df contents.

In [ ]:
```
for i in np.random.choice(corpus_df.index.values, 4):
    print(corpus_df.label.values[i])
    print(corpus_df.text.values[i], '\n\n')
```

Type *Markdown* and LaTeX: α^2

In [ ]:
```

```

In [ ]:
```

```

Process Input Data

Split Train and Holdout Data Sets

In [ ]:
```
x_train, x_holdout, y_train, y_holdout = train_test_split(
    corpus_df['text'],
    corpus_df['label'], test_size=0.1,
    random_state=random_state
)

train_df = pd.DataFrame(x_train, columns=['text'])
train_df['label'] = y_train

holdout_df = pd.DataFrame(x_holdout, columns=['text'])
holdout_df['label'] = y_holdout

train_df.reset_index(inplace=True)
holdout_df.reset_index(inplace=True)

print(train_df.shape[0], np.mean((train_df.label=='positive')*1))
print(holdout_df.shape[0], np.mean((holdout_df.label=='positive')*1))
```

Create Function to Vectorize Text

The functionality `scikit-learn` 's `CountVectorizer` (https://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.text.CountVectorizer.html) makes it really easy to transform words to text.

In [ ]:
```
def featurize_text(df, n_features=1000, max_df=0.50, min_df=50):

    vectorizer = CountVectorizer(max_df=max_df,
                                 min_df=min_df,
                                 max_features=n_features,
                                 stop_words='english')

    X = (vectorizer.fit_transform(df.text)>0)*1
    Y = (df.label=='positive')*1

    return X, Y, vectorizer
```

Inspect Vectorized Data

In [ ]:
```
X, Y, vectorizer = featurize_text(train_df, n_features=1000)
```

In [ ]:
```
word_df = pd.DataFrame(
    data = X.todense(),
    columns=vectorizer.get_feature_names()
)

count_df = pd.DataFrame(
    data = [word_df.sum(),
            word_df.loc[train_df.label=='positive'].sum(),
            word_df.loc[train_df.label=='negative'].sum()],
    index = ['total_count', 'pos_count', 'neg_count']
).transpose()

count_df['pos_share'] = count_df.pos_count/count_df.total_count*100
count_df['neg_share'] = count_df.neg_count/count_df.total_count*100
```

In [ ]:
```
(count_df[['total_count', 'pos_share', 'neg_share']]
 .sort_values(by='total_count', ascending=False)[:30])
```

Cross Validate Vectorization Parameters

Here we use `scikit-learn` to train a naive bayes classifier to rate the sentiment of each movie review. For more details of `scikit-learn` see here (https://scikit-learn.org/stable/modules/naive_bayes.html).

- What are the hyperparameters for this model?
- Does it makes sense to train more than one?
- What should we expect to see from our learning curves? Will more words overfit?

In [ ]:
```
k_fold = KFold(n_splits=5, random_state=random_state)
```

In [ ]:
```
def get_cv_results(df, n_features=1000, max_df=0.80, min_df=50):

    nbayes = BernoulliNB()
    X, Y, _ = featurize_text(df, n_features, max_df, min_df)

    results = []
    for train, test in k_fold.split(X):
        nbayes.fit(X[train, :], Y[train])
        y_predicted = nbayes.predict(X[test, :])
        accuracy = accuracy_score(Y[test], y_predicted)
        results.append(accuracy)

    return np.mean(results), np.std(results)
```

In [ ]:
```
get_cv_results(train_df)
```

In [ ]:
```
hp_values = [100, 250, 500, 750, 1000, 1500, 2000, 2500, 3000, 3500, 4000]
all_mu = []
all_sigma = []

for m in hp_values:

    mu, sigma = get_cv_results(train_df, n_features=m)
    all_mu.append(mu)
    all_sigma.append(sigma)

    print(m, mu, sigma)
```

In [ ]:
```
plt.figure(figsize=(14, 5))
plt.plot(hp_values, all_mu)
plt.ylabel('Cross Validation Accuracy')
plt.xlabel('Max Depth')
```

In [ ]:
```

```

In [ ]:
```

```

Train Optimal Model

In [ ]:
```
X, Y, vectorizer = featurize_text(train_df, n_features=2500)
nbayes = BernoulliNB()
nbayes.fit(X, Y)
```

Create Test Feature and Target Variables using the vectorizer we produced above.

- Why do we use the vectorizer produced above instead of creating a new one?

In [ ]:
```
X_test = vectorizer.transform(holdout_df.text)
Y_test = (holdout_df.label=='positive')*1

# Generate predicted labels (positive=1)
y_predicted = nbayes.predict(X_test)

# Generate predicted probabilities
y_probpos = nbayes.predict_proba(X_test)[:, 1]

print(X_test.shape)
```

Inspect in-sample performance.

In [ ]:
```
np.random.seed(random_state + 0)
for i in np.random.choice(holdout_df.index.values, 4):
    print('Index:           %i' % i)
    print('Prob. Positive:  %0.3f' % nbayes.predict_proba(X_test[i])[0][1])
    print('Label:           %s\n' % holdout_df.label.values[i])
    print(holdout_df.text.values[i], '\n\n')
```

Report Overall Out of Sample Performance

- Based on these results, do you think our classifier is overfitting?

In [ ]:
```
def report_performance(classifier):
    y_predicted = classifier.predict(X_test)
    print('No. of test samples:   %i' % len(y_predicted))
    print('Accuracy:              %0.1f%%' % (accuracy_score(Y_test, y_pred
    print('Precision:             %0.1f%%' % (precision_score(Y_test, y_pre
    print('Recall:                %0.1f%%' % (recall_score(Y_test, y_predic

report_performance(nbayes)
```

Examine our false positives

In [ ]:
```
np.random.seed(random_state + 0)
for i in np.random.choice(holdout_df.loc[(Y_test==0) & (y_predicted==1)].in
    print('Index:           %i' % i)
    print('Prob. Positive:  %0.3f' % y_probpos[i])
    print('True Label:      %s\n' % holdout_df.label.values[i])
    print(holdout_df.text.values[i], '\n\n')
```

Examine our false negatives

In [ ]:
```
np.random.seed(random_state + 0)
for i in np.random.choice(holdout_df.loc[(Y_test==1) & (y_predicted==0)].in
    print('Index:           %i' % i)
    print('Prob. Positive:  %0.3f' % nbayes.predict_proba(X_test[i])[0][1])
    print('True Label:      %s\n' % holdout_df.label.values[i])
    print(holdout_df.text.values[i], '\n\n')
```

Examine borderline cases

In [ ]:
```
np.random.seed(random_state + 0)

border_threshold = 0.05
borderline = ((y_probpos>(0.5-border_threshold)) &
              (y_probpos<(0.5+border_threshold)))
print('No. on border:   %i' % sum(borderline), '\n')

for i in np.random.choice(holdout_df.loc[borderline].index.values, 2):
    print('Index:           %i' % i)
    print('Prob. Positive:  %0.3f' % nbayes.predict_proba(X_test[i])[0][1])
    print('True Label:      %s\n' % holdout_df.label.values[i])
    print(holdout_df.text.values[i], '\n\n')
```

In [ ]:
```

```

Benchmark Against Other Models

- How will our performance with Naive Bayes live up to a logistic regression or gradient boosting machine?

In [ ]:
```
logreg = LogisticRegression(
    random_state=random_state,
    solver='lbfgs'
)

logreg.fit(X, Y)
report_performance(logreg)
```

In [ ]:
```
gbm = GradientBoostingClassifier(
    random_state=random_state,
    max_depth=6,
    n_estimators=100
)

gbm.fit(X, Y)
report_performance(gbm)
```

In [ ]:
```

```

In [ ]:
```

```

Take the classifier for a spin! Review a movie.

- Does our naive bayes classifier perform like we'd expect it to?
- How does it handle things like sarcasm? Negation?

To evaluate our classifier, we'll also rely on some additional reviews helpfully compiled by @AmznMovieRevws (https://twitter.com/AmznMovieRevws)

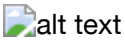
In [ ]:
```
def score_review(example, model):
    test = vectorizer.transform([example])
    print('Words included:  %i' % test.toarray().sum())
    print('Prob. Positive:  %0.3f' % nbayes.predict_proba(test)[0][1])
    print(example)
```

In [ ]:
```
example = '''
This was a really great movie. One of the best I've seen in a while!
'''

score_review(example, nbayes)
```

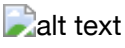
In [ ]:
```
example = '''
I hated this move. The plot was so slow and the acting was terrible.
'''

score_review(example, nbayes)
```



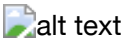
In [ ]:
```
example = '''
False Advertising. Don't be fooled. Although this movie is called "The Rock
entertainer Dwayne "The Rock" Johnson.
'''

score_review(example, nbayes)
```



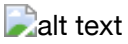
In [ ]:
```
example = '''
Misleading. There are no wolves in this movie.
'''

score_review(example, nbayes)
```



In [ ]:
```
example = '''
If you were going to see this movie because, like me, you love chocolate an
the process prepare to go elsewhere. This movie has no chocolate to offer -
chocolate, nothing about the abuses in the chocolate industry, and not even
I wish I were one of the dead characters in the movie, as I would have felt
'''

score_review(example, nbayes)
```



In [ ]:
```
example = '''
Expected a superhero named the tick to bite people and infect them with a s
Not impressed.
'''

score_review(example, nbayes)
```

In [ ]:
```
example = '''
There is nothing funny about a tick being a super hero. Ticks cause lyme di
'''

score_review(example, nbayes)
```

In [ ]:
```

```